Practice papers

# Leveraging financial personality for inclusive credit scoring amidst global uncertainty

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**Abstract** The Ukraine war, high inflation and rising interest rates are jeopardising people's ability to afford essential items such as food and energy, causing a widespread sense of vulnerability worldwide. Consequently, access to finance has become increasingly challenging for vulnerable consumer groups, including young adults without established credit histories, senior citizens with fixed incomes, start-up entrepreneurs, sole traders, single parents, immigrants in Western markets. To address this issue, this study explores the potential use of individuals' financial personality for inclusive credit scoring in these uncertain environments. Examining a sample of low-income individuals in the USA and the Netherlands, our psychometric scoring models (PSMs) demonstrate that late payments can be attributed to factors such as financial capability, materialistic tendencies, impulsive buying behaviour, social desirability and attitudes towards debt. These findings provide evidence that PSMs offer a viable solution to advance financial inclusion for vulnerable customer segments amidst global uncertainty.

**Keywords:** *access to finance, inclusive finance, behavioural finance, psychometric credit scoring, financial crisis, responsible lending*

## INTRODUCTION

To what extent can psychometrics advance inclusive finance among vulnerable customer segments in unstable Western economies post-COVID? Prior to the COVID-19 outbreak, approximately 2.5 billion individuals were already unbanked or underbanked.[1] The World Bank has recognised financial inclusion as a means to support seven out of the 17 sustainable development goals. The global financial crisis caused by COVID-19, along with forthcoming macroeconomic instability, has further amplified financial vulnerability and imposed additional barriers to financial access for vulnerable customers.[2] Vulnerable customers are individuals who, due to personal circumstances, are at risk of financial harm, particularly when businesses fail to provide them with adequate care.[3,4] The British Financial Conduct Authority (FCA) regards an individual's health, life events, resilience and capabilities as the primary factors influencing their present or future vulnerability.[5] In a poll conducted by the Associated Press in October 2022, it was found that 46 per cent of US adults describe their financial situation as poor due to high inflation.[6] Similar levels of financial vulnerability are observed in Western Europe.[7,8] This includes young adults, senior citizens with fixed incomes, start-up entrepreneurs, sole traders, small business owners, immigrants, individuals whose illnesses impact their earning capacity, those affected by natural disasters such as extreme heat, fires or floods, etc. A recent survey conducted by the FCA on customer vulnerability revealed that COVID-19 has disproportionately affected specific population groups, including younger adults and the self-employed.[9] As indicated in Table 1, more than 100 million Americans and 90 million Europeans are categorised as vulnerable. They rely on access to credit as a crucial necessity for improving their financial prospects and achieving upward mobility.[10]

The concept of vulnerability includes consumers who are prone to facing high credit costs and those excluded from conventional credit or financial services.[11] Moreover, a rising degree of financial hardship, marked by individuals taking on debt obligations under a contract but subsequently struggling to meet them when they become due, serves as an indicator of their level of financial vulnerability.[12] Limited or unstable income, which often results in being classified as high credit risk and having limited collateral, can lead to financial exclusion or result in high costs of credit in a tightly regulated financial environment.[13]

The regulatory framework for credit scoring systems in the USA and most European countries however differs significantly. In contrast to the United States, most European countries follow a negative credit scoring system, wherein only unpaid debts are recorded. To examine the effects of these macroeconomic credit scoring systems, this research focuses on two different systems: the positive credit scoring system in the USA and the negative credit scoring system in the Netherlands. Regardless of the system, lenders across both markets, including banks, credit card companies and alternative finance providers, still assess the creditworthiness of loan applicants. They utilise these credit scores to evaluate

**Table 1:** Vulnerable income segments Sources: Eurostat (https://ec.europa.eu/eurostat/data/database) and Semega *et al.*, 2020

| | EU | USA |
|---|---|---|
| Number of people (million) | 445 | 328.2 |
| Number of low-income households (million) | 43 | 53 |
| Number of self-employed workers (million) | 23.4 | 44 |
| Number of micro, small and medium-sized enterprise entrepreneurs (million) | 24.7 | 30.7 |

the potential risk involved in lending money to customers and minimise losses resulting from bad debts. Credit scoring comprises predictive models and techniques employed by financial institutions to determine creditworthiness.[14] It involves formal statistical methods that classify credit applicants into 'good' and 'bad' risk categories.[15] In the USA, a credit score is a numerical representation of the likelihood of individuals repaying their bills, derived from statistical analysis of their credit files. These statistical models predicting credit risk utilise predictor variables such as age, income, marital status and other conventional data to estimate the probability of defaulting.[16] We contend that relying on conventional data excludes vulnerable customer segments from financial services because many of them lack traditional financial and credit information. Recent research suggests that alternative data sources such as OB-based payment models,[17] mobile phone data[18–21] and social media data[22–25] yield significantly improved predictive credit performance and repayment likelihood compared to traditional credit scoring models. In this study, we investigate the potential benefits of incorporating psychometric data into the development of financial profiles to improve access to finance in the current market context.

Other recent studies suggests that AI-enabled profiles assist lenders in better understanding consumer behaviours and subsequently assessing the likelihood of loan repayment, thereby reducing the lender's risk when granting loans.[26] The dominant metric for model quality in the USA is the Kolmogorov-Smirnov index (KS),[27] which shows the accuracy of a default prediction by comparing the cumulative good customers with the cumulative bad ones. Most European lenders, however, apply the Gini coefficient as the leading metric for measuring model quality. The Gini coefficient indicates the credit model's discriminatory power, namely its efficiency in discriminating between good borrowers who will not default in the future and bad borrowers who will. The Gini coefficient applied in risk modelling equals Somers' D, which is a measure of the ordinal relationship between the model's probability of default and the actual outcome.[28] Somers' D is a summary of the cumulative accuracy profile curve and takes a value between –1 and 1; –1 being a perfect negative relationship, 0 being a random relationship and 1 being a perfect positive relationship. In practice, a credit score model with a Somers' D of 0.4 is considered a good model.[29] Regardless of the differences in the underlying statistics of these metrics, both American and European lenders assess the creditworthiness of their applicants and evaluate the predictive power of their models contentiously. In this study, we develop a novel logistic regression model with the dual objectives of achieving the highest predictive accuracy while adhering to regulatory requirements, such as explainability.

With growth and change come concerns about protecting consumers from firm exploitation due to imperfect information and contracting as well as from their own decision-making limitations.[30] In the USA, the Fair Credit Reporting Act (FCRA) regulates credit reporting agencies and compels them to ensure that the information they gather and distribute is a fair and accurate summary of a consumer's credit history. The FCRA is chiefly concerned with the way credit reporting agencies use the information they receive regarding one's credit history. The law is intended to protect consumers from information being used against them. It offers very specific guidelines on the methods that credit reporting agencies can use to collect and verify information and outline the reasons for the release of information. Vulnerable customers have issues accessing finance because of their less favourable credit ratings.[31] A favourable credit rating is necessary to obtain a credit card, purchase a home or car, start a new business, seek higher education or pursue other important goals such as access to employment, rental housing and insurance.[32] Nevertheless, numerous vulnerable customers possess either no credit history or a low credit score. In Europe, the European Securities and Market Authority (ESMA) oversees credit rating agencies and the associated credit rating agency regulation (CRA). The CRA is designed to enhance the integrity, responsibility, good governance and independence of credit rating activities to ensure quality ratings and high levels of investor protection. Hurley and Adebayo[33] argue, however, that individuals have very little control over how they are scored and have even less ability to contest inaccurate, biased or unfair assessments of their credit. Traditional, automated credit-scoring tools raise longstanding concerns regarding accuracy and unfairness. We argue that traditional credit scoring models are forces of financial exclusion due to their stringent focus on financial and credit data. However, also in our opinion, Hurley and Adebayo[34] rightfully conclude that the recent advent of new 'big-data' credit-scoring products heightens these concerns. Moreover, the uncertainty of the impact of the unprecedented COVID-19 pandemic on traditional credit score cards and credit decision-making makes the development of different responsible credit score models for granting credit to vulnerable customer segments urgent.

Therefore, the purpose of this study is to develop a credit rating system that enables responsible lending to vulnerable customers in the regulatory context of the USA and the Netherlands, utilising alternative psychometric data sources in addition to the traditional credit score data they often lack. While there is consensus on the significance of consumers' access to finance for their financial well-being, recent events such as severe heatwaves, floods, the COVID-19 pandemic and the energy crisis have emphasised the prevalence of vulnerability, prompting the need to address essential underlying questions. For instance, in the face of changing circumstances and outdated traditional credit score data, how can we distinguish between good and bad payers among vulnerable customers in these changing market conditions? What are the stable personality traits that contribute to favourable payment behaviour? In this research, we investigate these questions and identify the essential factors required to create a credit scoring system specifically designed for vulnerable consumers in Western economies. This will help us test our central hypothesis:

## PSYCHOMETRIC CREDIT SCORING INCREASES ACCESS TO FINANCE FOR VULNERABLE CONSUMER SEGMENTS ACROSS THE USA AND THE NETHERLANDS IN UNSTABLE MARKET CONDITIONS

### Vulnerability and big data

Generally speaking, customer vulnerability refers to situations in which customers do not engage effectively with their financial service providers and, as a result, put themselves at risk.[35] Vulnerability can manifest in various ways, including being temporary, permanent, gradual or sudden.[36] It can also be subjective, influenced by beliefs and attitudes, or objective, influenced by external factors such as debt and credit.[37] Similar to a credit score, customers' financial well-being fluctuates based on their financial management.[38] However, vulnerability can be broadly classified into two categories: driven by personal situations or market-specific circumstances.[39]

The United Kingdom's Financial Conduct Authority, one of the world's front-runner financial authorities, has identified a number of causes of actual or potential vulnerability from personal circumstances, including health problems (physical or mental), negative life events, resilience to shocks and inability to deal with financial matters.[40] The CMA also includes physical disability or low income. Customers who are often in significant debt are more likely to fall behind on their household bills or credit card payments. They are also excluded from accessing financial services, such as loans. Poor or no credit scores and large debts lead them to be high-risk customers. Due to financial exclusion, these individuals may never gain a digital or financial footprint to indicate how well they have managed their finances. Without a financial identity, they continue to be excluded.

Furthermore, access to financial services can be further inhibited by a lack of mobile phone, Internet connection or technological skills. Market-specific vulnerability is due to market contexts that limit access to financial services.[41] Moreover, the COVID-19 pandemic is an instigator of market-specific vulnerability that exacerbates inequality on a global scale.[42] However, in recent years, banks have seen technology as a tool to boost their competitiveness. For example, Poppleton *et al.*[43] state that technology continues to significantly impact the home mortgage sector of retail banking. FinTech embraces technology to deliver an alternative to traditional banking and is expected to extend financial market reach to those that are excluded and underserved.[44] FinTech generates a comprehensive data view of customers refined by artificial intelligence (AI) to improve customer offerings and experiences. FinTech is, therefore, transforming financial inclusion on a long-term, large-scale basis. Consequently, the credit-scoring industry has experienced a recent explosion of start-ups that take an 'all data is credit data' approach, combining conventional credit information with thousands of data points mined from consumers' offline and online activities.[45]

Big data scoring tools may now base credit decisions on where people shop, the purchases they make, their online social media networks and various other factors that are not intuitively related to their credit scores.[46] Therefore, national governments protect financial consumers against transparency, privacy and data breaches by maintaining regulations such as the General Data Protection Regulation (GDPR) in Europe[47] and the California Consumer Privacy Act (CCPA) in California.[48] According to these American and European consumer protection directives, consumers have the right to make informed decisions, the right to choose and change their mind, the right to pay back ahead of time, the right to be safe and to be heard. However, are all customers capable of doing so? In the American and European consumer credit directives, it is required that creditors do not engage in irresponsible lending. Moreover, they should bear the responsibility of individually checking the vulnerability of each consumer. Nevertheless, there is evidence that some types of financial services, such as payday loan lenders, online gambling firms and online travel agents exacerbate and add to customer vulnerabilities.[49] Since they lack credit scores in the customer aggregate data, vulnerable customers cannot access fair deals, which leads to adverse and negative impacts on these customers. For example, when vulnerable customers access a financial product, they may face higher charges than better-off customers,[50] such as high-interest loans or high premiums on insurance.

With consumer protection in mind, using non-traditional data for credit scoring might benefit financial inclusion. Extant findings, for example, indicate that mobile phone data such as call detail records, device features, mobility features and airtime recharge are at least as good in predicting customer payment behaviour as traditional data.[51–54] Additionally, social media data such as someone's activity, texts, photos and videos, network density and someone's centrality in the network have been a research focus for credit scoring.[55–58] Customer protection regulations in Western countries, however, forbid lenders to use these data sources for credit decision-making because of customer privacy and transparency.

Given that vulnerable customers, especially in the context of the economic consequences of high inflation, natural disasters and the COVID-19 pandemic, need novel credit scoring solutions to increase their access to finance, we aimed to identify transparent alternative drivers that correlate with their payment behaviour. Inspired by venture capital investors — hampered by the lack of reliable data for predicting their investment risk and having to place the quality of the founding team at the centre of their seed and early-stage investments for decades[59] — we investigated personality data to predict payment risks. As we describe in the literature section of this paper, many other studies have shown the direct effect of personality traits on financial behaviours, but few have focused on the holistic psychometric profile construct to predict payment behaviour. Klinger *et al.*[60] however, found the predictive value of psychometric features for predicting the credit risk of small businesses in Peru. Their credit scoring model for Peruvian small businesses was built on the Big 5 personality model,[61] as well as measures of intelligence, numeracy and integrity.[62–64]

## Influence of financial personality on financial behaviour

Although a lot of research has been performed on individual behavioural traits and financial behaviour, a holistic approach is lacking. Nevertheless, we made use of existing literature on the influence of financial personality on financial behaviour and debt to establish a conceptual model with constructs that may influence late payment behaviour. First, consumers' ability to make informed financial decisions improves their ability to develop sound personal finance.[65] Therefore, many studies have investigated the relationship between financial literacy and financial decision making.[66] Financial illiteracy appears to be particularly severe for key demographic and often vulnerable groups: women, those less educated, those with low income, ethnic minorities and older respondents.[67–71] The term financial literacy has been used loosely and is used both to describe financial knowledge and financial skills.[72] Financial knowledge is the most common definition of financial literacy. It is based on the idea that for effective money management, people must understand how money works. Examples of financial knowledge include understanding the mechanisms of compound interest, collaterals and credit history. Besides financial knowledge, financial skills (sometimes referred to as financial behaviour) are also considered to be part of financial literacy.[73] Financial skills concern the ability to perform tasks related to money management, such as budgeting and tracking expenses. Better financial skills are associated with higher savings and lower debt.[74,75] We argue that vulnerable customers are often financially illiterate and poorly financially skilled and therefore, often end up with financial problems. Therefore, we include financial skills as the first construct in our conceptual model and argue that it has a negative correlation with arrears.

Moreover, recent research on vulnerable customers shows that one of the personal characteristics that drives vulnerability is impulsive buying.[76] Additionally, researchers found that people with low self-control tend to engage more in compulsive buying and have more debt,[77] whereas people with high self-control are more likely to save money from each paycheck.[78] Moreover, Norvilitis *et al*.[79] found that having difficulties delaying gratification has been related to having a higher amount of debt and problematic gambling.[80] Gratification refers to the process in which a person foregoes an immediate reward in order to receive a larger reward later. We therefore add gratification as the second variable to our conceptual model and argue a positive correlation.

Other debt-related research reveals that students get into deeper debts because they overestimate how much they will earn after they graduate.[81] Consumers are also more likely to get a new credit card if they think it is easy to repay the balance.[82] In short, consumers take high risks because they are too confident.[83] The term (over)confidence is used in at least three ways: to describe overestimation, over placement and calibration of subjective probabilities.[84,85] The first definition refers to the overestimation of one's achievements, actual ability or chance of success in comparison to one's actual performance, ability or success. For example, a person's actual score on a test is compared to that person's estimate of their score. The second definition, over placement, refers to the comparison between a person's achievements and the performance of others. That is, the type of overconfidence that occurs when people think they are better than others. For example, a person's estimate of their rank (compared to others) is compared with their actual rank. Lastly, the calibration of subjective probabilities (also referred to as over precision or realism of confidence) refers to the comparison of someone's subjective probabilities with actual objective probabilities. Based on these earlier debt-related research findings we also add confidence to our conceptual model and postulate a positive correlation with debt and therefore also with arrears.

Other research on student and household debt shows that more positive attitudes toward debt are associated with more debt.[86,87] Moreover, they found that there were two different types of attitudes associated with debt. On the one hand, having more fear of debt was associated with less debt, whereas seeing the utility of debt was associated with more debt. We argue that vulnerable customers with positive attitudes towards debt face a high risk of indebtedness, consequently leading to payment difficulties. Therefore, we also add debt attitude to our conceptual model and hypothesise a positive correlation with arrears.

Previous studies also have consistently found a relationship between materialistic value and debt.[88,89] Materialism is the extent to which people value the acquisition and consumption of material objects.[90] Moreover, research has shown that there are two scales that measure individual differences in materialism. The first scale is the Material Values Scale,[91,92] which operationalises materialism as a set of values related to acquisition centrality, acquisition as the pursuit of happiness and possession-defined success. The second scale is the Trait Materialism Scale,[93] which assesses three aspects of materialism: possessiveness, non-generosity and envy. Based on these studies we add materialism to our conceptual model and argue a positive correlation with debt and arrears.

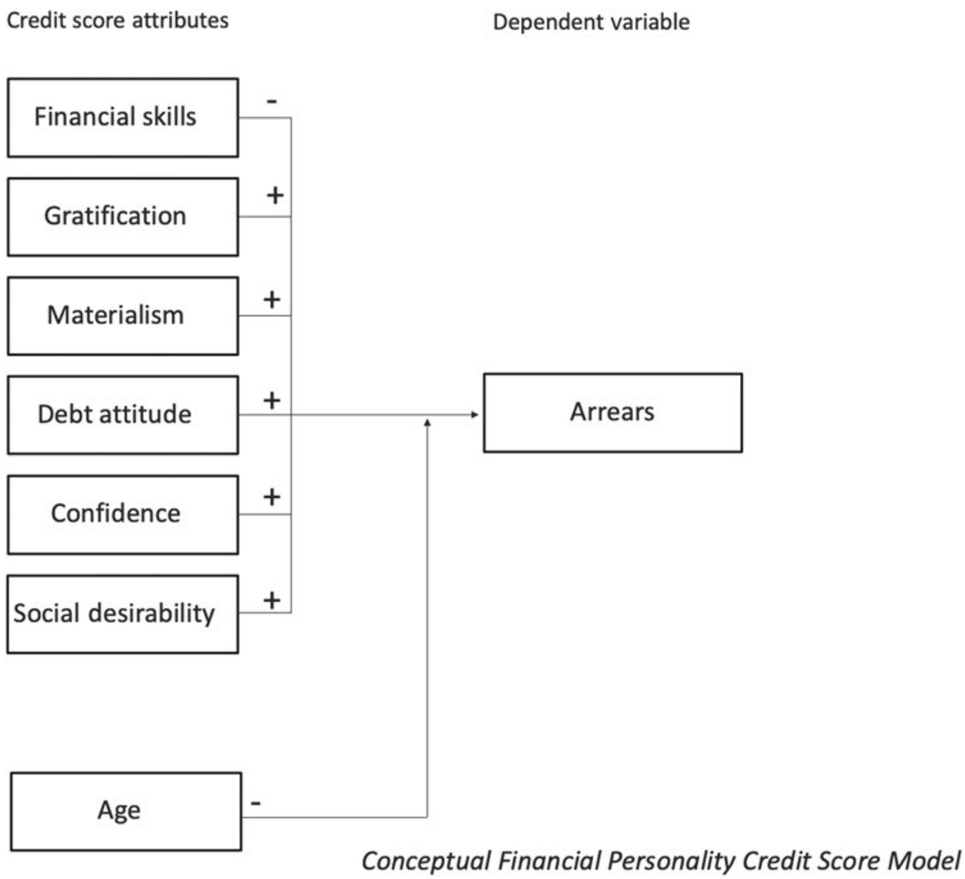


**Figure 1:** Conceptual model

The issue with the materialism scales is that they are based on questionnaires that consequently show self-reported insights in which people tend to present themselves more favourably. This phenomenon is called social desirability.[94] There are two types of socially desirable responses: a person may actually believe the reported information (self-deception) or a person may fake information to conform to the norm. Answering in a socially desirable way can lead to spurious correlations and to the moderation or suppression of the relationship between the researched constructs.[95] Although Norvilitis *et al.*[96] do not measure social desirability, they state that it might influence whether people report their debt. In our research, we add social desirability to our conceptual model too and hypothesise a positive correlation with debt and arrears.

Based on earlier research on customer vulnerability and personal drivers of debt, we develop a financial lifestyle framework to predict payment behaviour. We incorporate the demographic variable of age into the financial lifestyle framework to account for an individual's life experience and its negative relation with arrears. The conceptual model provides a holistic view on the personality drivers that predict debt. Based on our research to psychometric credit scoring, we hypothesise a positive correlation between gratification, materialism, debt attitude, confidence and social desirability and arrears. Moreover, we hypothesise a negative correlation between financial skills, age and arrears. The framework is shown in Figure 1.[97]

## The present research

In light of the literature discussed in this paper, our research entails a cross-country study involving two nations with distinct credit scoring systems. The objective is to assess how the psychometric constructs we have explored impact the late payment behaviour of financially vulnerable consumers during periods of market instability. In our novel conceptual model, we postulate that the financial literacy related attributes exert an influence on payment behaviour (the dependent variable) in a manner consistent with existing research.

Utilising an integrated dataset from our study in these two countries, we have devised and validated a psychometric credit scoring model that can be applied across the two countries. This model facilitates responsible credit extension to customer segments facing financial vulnerability. Our central research question seeks to identify which personality traits are pertinent in gauging the creditworthiness of vulnerable customers within Western economies. A visual representation of the conceptual psychometric model can be found in Figure 1.

The choice of research countries, namely the United States and the Netherlands, was deliberate. We selected them due to their well-regulated credit decision-making processes and advanced levels of digitalisation. Furthermore, the presence of a competitive landscape encompassing traditional lenders, FinTech lenders and big tech lenders was a pivotal criterion for our selection.

## DATA AND METHOD

### Data collection

Between January 2019 and October 2019, we gathered survey data from a random sample of low-income applicants (*N*=897) drawn from Dynata research panels in both the USA (*N*=694) and the Netherlands (*N*=203). Our selection of respondents was focused on two well-regulated banking markets with a high level of digital adoption. The Dutch study was conducted during the first quarter of 2019, while the US study was carried out in the third quarter of 2019. A summary of our sample is provided in Table 2.

Our criteria for selecting low-income participants involved an annual income of €25,000 and US$25,000 for individuals residing in the Netherlands and the USA, respectively, and being residents of these countries. We extended invitations to potential respondents via e-mail for participation in the online research and upon completion and submission of the questionnaire, participants were rewarded with €30/$30 gift cards. We took precautions to mitigate the influence of this reward by incorporating a 'social desirability' feature. The respondents, on average, had an age of 38-years-old, with approximately 50 per cent being male, mirroring the market demographics. A comparison with market averages is detailed in Table 3, derived from each country's central statistics bureaus. Notably, 23 per cent of participants were married, which falls below the market average, while 43 per cent were single, representing the market accurately. However, 43 per cent of participants reported one-person households, indicating an over-representation of such households. Of the total participants, 58 per cent reported having children, which aligns with the US market but over-represents the situation in the Netherlands. The demographic breakdown of the data is outlined in Table 3.

**Table 2:** Dataset

| Country | Data sources | | |
|---|---|---|---|
| | Respondents | Arrears | Non-arrears |
| USA | 694 | 163 | 531 |
| Netherlands | 203 | 100 | 103 |
| Total | 897 | 263 | 634 |

The AdviceRobo team developed a digital psychometric questionnaire, incorporating the specified psychometric attributes and age. This questionnaire consisted of 17 questions featuring a five-point Likert scale response or binary format. The survey aimed to collect information regarding participants' financial skills, gratification tendencies, materialism, attitudes toward debt, confidence levels, social desirability and their demographic details. Before starting the study, Cronbach's $\alpha$ of all the survey questions was tested. Table 4 presents the psychometric survey questions and their correlations with instances of arrears.

To assess the latent constructs of financial skills, gratification, materialism, debt attitudes, confidence and social desirability, a five-point Likert scale was employed for each question in the survey. The responses from the survey were normalised using minmax normalisation and compiled into a dataset

**Table 3:** Respondents Sources: Central Bureau of Statistics, 2019 and Pew Research, 2021, https://www.pewresearch.org/short-reads/2021/11/03/the-self-employed-are-back-at-work-in-pre-covid-19-numbers-but-their-businesses-have-smaller-payrolls/)

| | Sample | USA market | Dutch market |
|---|---|---|---|
| Age (average) | 38 | 38.5 | 42.8 |
| Sex | 52% male/ 48% female | 49% male/ 51% female | 49% male/ 51% female |
| Income (average) | $/€ 25,000, - | $ 35,977, - | € 36,500, - |
| Married | 23% | 75% | 39% |
| Single | 43% | 31% | 38% |
| Household with children | 58% | 56% | 33% |
| Internet penetration | 100% | 96% | 98% |

**Table 4:** Survey questions and correlation with arrears

| Question | Arrears |
|---|---|
| I am guided by my immediate desires and do not dwell on what the future may look like. | 0.11 |
| My convenience is a big factor in the decisions I make or the actions I take. | –0.08 |
| I don't think about future problems because I think the future will take care of itself. | –0.08 |
| Sometimes I forget to pay my bills on time. | 0.02 |
| If I have an incidental expense, I have enough savings to cover the expense. | 0.07 |
| I admire people who own expensive homes, cars and clothes. | 0.10 |
| I place much emphasis on the amount of material objects people own as a sign of success. | –0.01 |
| I like to own things that impress people. | 0.09 |
| It is easy for me to stick to my aims and accomplish my goals. | 0.13 |
| I can stay calm if I have problems because I trust myself that I can handle it well. | 0.01 |
| When I am confronted with a problem, I can usually find several solutions. | 0.19 |
| Taking out a loan can be a good thing, if it helps people to enjoy their life. | 0.07 |
| For many people, debt is a normal part of life. | 0.11 |
| In today's society, it is almost impossible to live without debts. | 0.11 |
| I sometimes feel resentful when I don't get my way. | 0.03 |
| There have been occasions when I felt like smashing things. | –0.21 |
| There have been times when I was quite jealous of the good fortune of others. | –0.10 |

denoted as $DS = X^1, X^2, \ldots, X^n$, which encompassed both demographic information and participants' responses. Table 5 provides statistics pertaining to the answers.

## Methodology

To examine the association between the newly devised conceptual psychometric model attributes and payment behaviour, respondents were queried about any instances of overdue payments within the past year for five distinct bill categories: health insurance, mortgage/rent, energy, water and phone bills. If respondents reported arrears in at least one of these five categories within the past year, they were classified as having arrears. Otherwise, they were categorised as having no arrears. To ensure the accuracy of these classifications, we cross-validated them with credit bureau data, revealing no discrepancies. In our research, good payment behaviour was defined as having no arrears, while customers exhibiting arrears were considered to have poor payment behaviour.

**Table 5:** Statistics from the questionnaire responses

| Question | Mean | Standard deviation |
|---|---|---|
| Gratification 1 | 2.67 | 1.11 |
| Gratification 2 | 3.30 | 0.95 |
| Gratification 3 | 2.62 | 1.10 |
| Financial skills 2 | 3.87 | 1.25 |
| Financial skills 3 | 3.47 | 1.38 |
| Materialism 1 | 2.78 | 1.20 |
| Materialism 2 | 2.25 | 1.01 |
| Materialism 3 | 2.48 | 1.17 |
| Confidence 1 | 3.55 | 0.95 |
| Confidence 2 | 3.73 | 0.96 |
| Confidence 3 | 3.89 | 0.83 |
| Debt attitude 1 | 2.85 | 1.11 |
| Debt attitude 2 | 3.68 | 1.00 |
| Debt attitude 3 | 3.40 | 1.15 |
| Social desirability 1 | 0.52 | 0.50 |
| Social desirability 2 | 0.50 | 0.50 |
| Social desirability 3 | 0.53 | 0.50 |

Additionally, we conducted a principal component analysis with Varimax rotation to evaluate the questionnaire's structure, which involved merging questions from different sources. This step aimed to reduce potential multicollinearity among the questions. By applying principal component analysis and employing a selection criterion of eigenvalues exceeding 1, we identified components predictive of arrears. The outcome was a comprehensive principal component model consisting of five components. Subsequently, to formulate an international personality-centric credit decision-making model for predicting arrears (referred to as the IPSYCRED model), we conducted logistic regression. To train and validate this model, we divided the dataset into a training set (70 per cent) and a test set (30 per cent). Our analysis involved examining whether the model could statistically incorporate the factors as variables, excluding any coefficients with zero reliability at a 95 per cent confidence level. The result of this regression analysis yielded a five-factor psychometric credit scoring model. Lenders can utilise this model in their application processes, particularly for vulnerable and thin-file customer segments, to differentiate applicants based on their projected payment behaviour.

# RESULTS

## Principal component analysis

To construct a cross-country logistic regression personality-centric model for predicting payment behaviour, we initially evaluated the eigenvalues to determine the appropriate number of components. Our criterion was to select components with eigenvalues exceeding one, resulting in the inclusion of five components in the international model. These components collectively account for 57 per cent of the variance, a suitable coverage for credit scoring purposes. Table 6 displays the eigenvalues of the international financial personality model.

Subsequently, we conducted a principal component analysis to assess the data's structure, reduce potential collinearity and streamline features. The international principal component analysis findings are summarised in Table 7.

The principal component table provided reveals that the first component embodies a fusion of financial skills and confidence, appropriately labelled 'financial acumen'. This component illuminates individuals' ability to make sound financial decisions and the degree of confidence they have in those decisions. The second component is centred on materialism, reflecting the extent to which respondents value material possessions they aspire to attain. Individuals in this segment are referred to as 'materialistic magnates'. The third component, termed 'impulse control', assesses impulsive buying tendencies and the capacity for self-control in delaying expenditures. The fourth component, designated as 'financial vulnerable optimists', displays a positive correlation with debt attitudes and a negative association with financial preparedness for unexpected events. Lastly, the fifth component, known as 'emotionally spending propensity', underscores social desirability, functioning as a measure of respondents' inclination towards social desirability bias and serves as a control variable in our credit scoring model. Table 8 offers an overview of these principal components and their interpretations.

**Table 6:** Eigenvalues and explained variance

| Component | Initial eigenvalues | | | Rotation sums of squared loadings | | |
|---|---|---|---|---|---|---|
| | Total | % of variance | Cumulative % | Total | % of variance | Cumulative % |
| 1 | **3.214** | 18.907 | 18.907 | 2.290 | 13.468 | 13.468 |
| 2 | **2.300** | 13.527 | 32.434 | 2.082 | 12.244 | 25.712 |
| 3 | **1.623** | 9.546 | 41.980 | 1.953 | 11.487 | 37.199 |
| 4 | **1.392** | 8.188 | 50.168 | 1.774 | 10.435 | 47.634 |
| 5 | **1.193** | 7.017 | 57.185 | 1.624 | 9.551 | 57.185 |
| 6 | 0.915 | 5.383 | 62.568 | | | |
| 7 | 0.820 | 4.823 | 67.392 | | | |
| 8 | 0.730 | 4.295 | 71.687 | | | |
| 9 | 0.706 | 4.153 | 75.839 | | | |
| 10 | 0.654 | 3.847 | 79.687 | | | |
| 11 | 0.606 | 3.566 | 83.253 | | | |
| 12 | 0.582 | 3.421 | 86.674 | | | |
| 13 | 0.559 | 3.291 | 89.965 | | | |
| 14 | 0.485 | 2.850 | 92.815 | | | |
| 15 | 0.433 | 2.549 | 95.363 | | | |
| 16 | 0.405 | 2.384 | 97.748 | | | |
| 17 | 0.383 | 2.252 | 100.000 | | | |

**Table 7:** International principal component analysis

| Question | Component 1 | Component 2 | Component 3 | Component 4 | Component 5 |
|---|---|---|---|---|---|
| Gratification 1 | | | 0.80 | | |
| Gratification 2 | | | 0.55 | | |
| Gratification 3 | | | 0.79 | | |
| Financial skills 2 | 0.38 | | | –0.45 | |
| Financial skills 3 | 0.59 | | | | |
| Materialism 1 | | 0.73 | | | |
| Materialism 2 | | 0.79 | | | |
| Materialism 3 | | 0.78 | | | |
| Confidence 1 | 0.73 | | | | |
| Confidence 2 | 0.74 | | | | |
| Confidence 3 | 0.76 | | | | |
| Debt attitude 1 | | | | 0.58 | |
| Debt attitude 2 | | | | 0.68 | |
| Debt attitude 3 | | | | 0.72 | |
| Social desirability 1 | | | | | 0.70 |
| Social desirability 2 | | | | | 0.69 |
| Social desirability 3 | | | | | 0.71 |

 

**Table 8:** Principal components and their meanings

| Principal Component | Name | Meaning |
|---|---|---|
| Component 1 | Financial acumen | The ability to make financial decisions that one trusts |
| Component 2 | Materialism | The desire for material things |
| Component 3 | Impulse control | The level of impulsive buying or controlled spending |
| Component 4 | Financial vulnerable optimism | The openness for debt while having no buffer |
| Component 5 | Emotional spending propensity | The level of social desirability bias |

## Logistic regression decision modelling

In our pursuit of enhancing credit decision making for vulnerable and thin-file customer segments, we trained a predictive logistic regression model. Despite the availability of more advanced artificial intelligence models, we opted for logistic regression due to compliance considerations. Western countries impose rigorous regulatory requirements on credit scoring models, emphasising their explainability and transparency. Furthermore, we encountered issues of overfitting when employing more advanced methods.

In this approach, we selected late payments as the dependent variable, a binary variable with positive and negative classes, enabling lenders to accept or reject applicants. From the five ordinal explaining components identified in the principal component analysis, we chose to exclude component 2, 'materialism', as it had a *p*-value greater than 0.5. Utilising these components, we partitioned the data into a training set (70 per cent) and a test set (30 per cent) and trained a logistic regression model using Python Jupyter 6.0.0 notebook. The selection of the cut-off point for accepting or rejecting prospects was determined through the receiver operating characteristic (ROC) curve analysis, with the best fit logit model summarised in Table 9.

The resulting international psychometric model can be represented as:

$$\text{Log (arrears)} = -0.79 - (0.76 \star \text{financial acumen}) + (0.72 \star \text{financial vulnerable optimism}) + (0.50 \star \text{impulse control}) - (0.28 \star \text{emotional spending propensity}) - (0.01\ \text{age})$$

It is important to acknowledge that the moderate R-squared value and the near parity between the intercept's beta and some other betas may be attributed to the skewed dataset with a limited number of arrears.

Nonetheless, we expect that this model will provide value to credit scoring, given that the

**Table 9:** Logit regression results

| **Logit regression results** | | | | | | |
|---|---|---|---|---|---|---|
| Dependent variable | | Arrears | | No observations | | 627 |
| Model | | Logit | | Df residuals | | 621 |
| Method | | MLE | | Df model | | 5 |
| Pseudo R-square | | 0.1746 | | Log likelihood | | –310.28 |
| LL-null | | –375.90 | | LLR-*p*-value | | 1.296e–26 |
| **Component** | **Coefficient** | **Std error** | **z** | ***P* > \|z\|** | **[0.025** | **0.975]** |
| Intercept | –0.7851 | 0.319 | –2.459 | 0.014 | –1.411 | –0.159 |
| PC1 | –0.7577 | 0.111 | –6.844 | 0.000 | –0.975 | –0.541 |
| PC4 | 0.7233 | 0.113 | 6.427 | 0.000 | 0.503 | 0.944 |
| PC3 | 0.5031 | 0.103 | 4.869 | 0.000 | 0.301 | 0.706 |
| PC5 | –0.2816 | 0.100 | –2.811 | 0.005 | –0.478 | –0.085 |
| Age | –0.0087 | 0.007 | –1.252 | 0.211 | –0.022 | 0.005 |

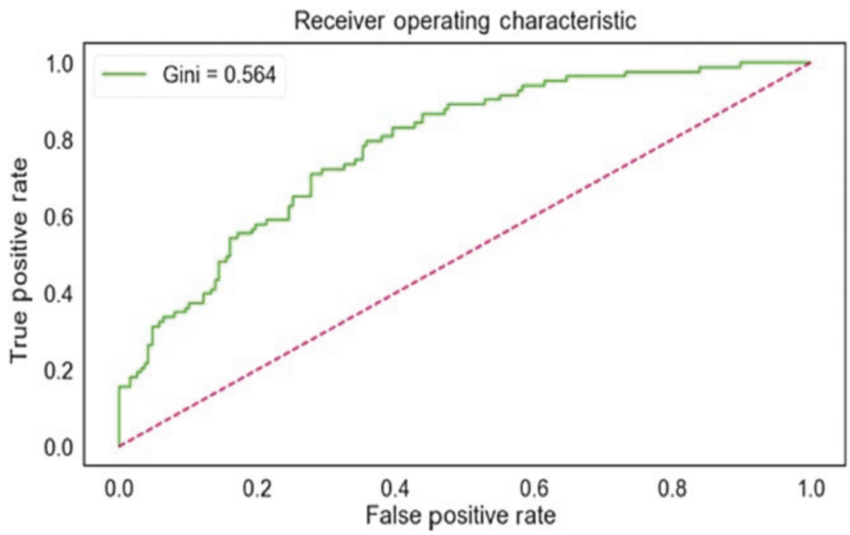


**Figure 2:** ROC – curve

individual predictor variables in the model demonstrate statistical significance. One of the model's objectives was to distinguish various attributes for personality-centric credit scoring. Furthermore, the attributes associated with the novel personality factors align with theoretical knowledge derived from prior research as discussed in the introduction.

To further assess the model's ability to predict arrears, we examined model metrics on the test set ($N=270$). Specifically, we analysed the area under the curve (AUC) and Gini score, widely recognised accuracy metrics as introduced in this paper. The decision model yielded an AUC of 0.78 and a Gini score of 0.56, which is reasonably strong considering that the model predicts late payments solely based on personality traits. The ROC curve is depicted in Figure 2.

To delve deeper into the model's accuracy on the test set, we examined the confusion matrix and derived statistics, as presented in Table 10.

The validation of the model's predictive power demonstrates its ability to correctly predict 70.7 per cent of instances. For lenders, the accurate prediction of which customers to accept holds significant importance for business models and pricing strategies. The model precisely predicts 72.2 per cent of good-paying customers and 67.5 per cent of actual arrears. Notably, for lenders, the correct prediction of arrears carries substantial implications, as late-paying customers incur significant costs. The model's precision in predicting arrears was 0.52, while its precision in predicting good customers stood at 0.83, indicating superior performance in identifying good customers.

**Table 10:** Observed and predicted frequencies for late payment by logistic regression

| Observed | Predicted non arrears | Predicted arrears | % correct |
|---|---|---|---|
| Non arrears | 135 | 52 | 72.2% |
| Arrears | 27 | 56 | 67.5% |
| Overall | | | 70.7% |

Furthermore, the model exhibited a recall of 0.675, signifying that it accurately predicted 67.5 per cent of all arrears. When focusing on the prediction of good customers, the recall was 0.72. While the model demonstrates a slight advantage in predicting good customers, it unquestionably enhances credit scoring, particularly in cases where financial data on applicants is limited or nonexistent.

In conclusion, these findings affirm the core hypothesis that financial personality-centric credit scoring enhances financial access for vulnerable consumer segments in both the USA and the Netherlands, especially under unstable market conditions.

## DISCUSSION

The objective of this study was to explore the hypothesis that financial personality-centric credit scoring could improve financial access for vulnerable consumer segments in the USA and the Netherlands, especially relevant during times of market instability. This research fills a crucial gap by emphasising the significance of financial personality factors in shaping payment behaviour when traditional financial data is scarce or outdated, as exemplified during crises like the COVID-19 pandemic or high inflationary market contexts. Our findings corroborate the core hypothesis and align with previous studies by Klinger *et al.*[98] and Hurley and Adebayo[99] emphasising the relevance of personality traits also in promoting financial inclusion of small businesses.

While prior research has focused on the impact of individual psychometric attributes on financial behaviour, this study represents a pioneering effort in merging financial literacy related personality attributes in unstable market contexts, resulting in the development of a comprehensive personality-centric logistic regression model for credit scoring in highly regulated markets. Furthermore, our research uncovered new psychometric components such as 'financial acumen' and 'financial vulnerable optimism'. Despite these novel findings, our results remain consistent with Lussardi and Mitchell's[100] assertion that financial knowledge plays a substantial role in financial inclusion, as hypothesised in our conceptual model. Nonetheless, our study opted for the use of financial skills instead of financial knowledge in predicting payment behaviour, drawing on Dew and Xiao's[101] findings that financial skills are linked to increased savings and reduced debt.

Notably, our research has shed light on the relationship between financial skills and confidence. While prior studies like those by Seaward and Kemp[102] and Nosić and Weber[103] highlighted the connection between overestimating future earnings and accumulating debt or engaging in high-risk behaviour, our findings underscore the pivotal role of financial skills in predicting payment behaviour. Individuals with moderate or low financial skills combined with overconfidence are more likely to exhibit delinquent payment behaviour, a crucial component with the most substantial impact in our logistic regression analysis ($\beta$-coefficient of 0.76).

Our study also aligns with earlier research by Davies and Lea,[104] Norvilitis *et al.*[105] and Haultain *et al.*,[106] which observed a positive link between positive debt attitudes and higher debt levels. Nevertheless, we identified a negative correlation between debt attitudes and the absence of savings when forecasting late payments. The interplay between various components within a comprehensive personality model, a unique aspect in behavioural financial research, significantly contributes to the prediction of payment behaviour. This component, which we call 'financial vulnerable optimism' has a $\beta$-coefficient of 0.72 and therefore stands as the second most influential factor. These findings pave the way for constructing financial personality profiles to distinguish between good and bad payers when extending loans, thus enhancing credit decision-making.

Additionally, we introduced social desirability as a control factor in our model, uncovering a relationship between the level of social desirability and expected payment behaviour ($\beta$-coefficient of 0.28). Our study is among the first to establish a predictive association between social desirability and payment behaviour. Furthermore, we found that age had a minimal impact ($\beta$-coefficient of $-0.01$) on late payments. The logistic regression model achieved an accuracy rate of 70.7 per cent and a Gini coefficient of 0.56. It demonstrates a slightly superior ability to predict good payment behaviour, underscoring its potential significance in credit scoring for vulnerable and thin-file customer segments in Western credit markets. Consequently, the model's predictive power substantiates financial inclusion efforts and mitigates information asymmetry.

Our research has also demonstrated that the credit score model can be applied across different countries and credit rating systems. While we discussed the aggregated model, we also developed location-specific models closely aligning with the aggregated one. Traditional credit decision-making approaches have been historically localised and costly. The internationally scalable credit decision model we propose can aid multinational lenders in improving cost/income ratios and accelerating the digitisation of credit assessment. We encourage the incorporation of real-time financial personality data from various sources such as open banking transactions, mobile phones, search engines and social media to further enrich lenders' understanding of new customers' psychometric profiles.

Additionally, we emphasise the importance of respecting privacy regulations when utilising personal behavioural data for customer qualification and risk mitigation strategies. In a post-COVID digital era, the number of vulnerable customers is anticipated to increase due to deteriorating economic and environmental circumstances. Even individuals previously considered financially stable can become vulnerable suddenly, whether due to crises, divorces or physical disabilities. The recovery process is particularly challenging for those already in vulnerable situations, leading to a rise in the overall number of vulnerable consumers. Hence, we contend that adopting novel credit decision-making approaches must align with customer protection regulations. In Western jurisdictions, contemporary regulators have instituted regulatory frameworks, like sandboxes, to assess innovative credit decisioning solutions tailored for these customer segments while ensuring adherence to regulatory and privacy standards. Our argument posits that these sandboxes should be employed as a preliminary step before introducing new solutions to the market, in order to evaluate their ethical and equitable qualities. Regulators are progressively embracing such initiatives aimed at mitigating vulnerability and curbing financial risks.

We encourage (neo)banks, credit card companies, insurers, utility providers and telecom companies to explore and implement personality data in their customer profiling, risk and marketing models. By doing so, they can deepen their understanding of customers, enhance their risk assessment and responsibly support these customer segments. We believe that these personality data are valuable for developing tailored solutions that promote financial well-being across a wide range of customer segments. Moreover, we also encourage the application of individual personality profiles to develop predictive personalisation strategies that mitigate late payment risks, enhance customer engagement and deliver added customer value. Additionally, we call upon regulators to consider incorporating financial personality data into their consumer protection strategies, which can help prevent anomalies such as students using loans to invest in stocks due to overconfidence or financial vulnerable optimists with limited impulse control obtaining loans or mortgages through self-service digital channels while maintaining a high level of financial vulnerability.

In conclusion, our research suggests that personality-centric credit models can be successfully adapted across Western countries with varying credit scoring systems. Our findings indicate that the financial personality construct is a reliable predictor of payment behaviour among vulnerable consumers. This is particularly pertinent in today's volatile market conditions. Confidence-driven financial skills emerge as the strongest predictor of positive payment behaviour. Furthermore, the ability to delay gratification and negative debt attitudes predict good payment behaviour. These findings hold consistent reliability across different countries. These key findings highlight the potential of financial personality profiling to responsibly facilitate access to finance for vulnerable customers in Western markets. We conclude by emphasising that psychometric models can very well serve as supplementary models, complementing traditional and alternative data sources while adhering to customer privacy regulations. To the best of our knowledge, this study represents the first comprehensive examination of psychometric personality profiles as predictors of payment risks among vulnerable customer segments in highly regulated Western credit markets.

## Limitations and future research directions

This study exhibits several limitations that warrant consideration. First, it is imperative to acknowledge that the data collection was confined to two Western nations, thereby limiting the scope of generalisability. To extend the applicability of our findings, future research should encompass a broader geographic spectrum, including developing countries. Such an approach could unveil opportunities for enhanced financial inclusion among vulnerable populations in these regions.

Secondly, our investigation relied on self-reported arrear information, cross-validated with credit bureau data spanning various product categories. To refine the precision and efficacy of predictive models, forthcoming studies should strive to acquire genuine behavioural data pertaining to diverse segments of vulnerable consumers.

Thirdly, the temporal dimension of our study introduces potential bias, given that data collection occurred prior to the onset of the COVID-19 pandemic in 2019. While psychometric traits are known for their stability over time, it is imperative to conduct supplementary research under post-pandemic market conditions to ascertain the persistence of observed trends.

Another limitation relates to the use of ordinal data for the purpose of rendering results comparable across models. Although Likert scales were employed to assess participants' financial skills, materialism, debt attitude, confidence, gratification and social desirability, these scales may inadvertently oversimplify individuals' nuanced psychological perceptions. Recognising that human experiences often defy rigid categorisation, future research endeavours should explore alternative digital data sources, such as open banking transaction records, social media data, mobile phone data, biometric data and search behaviour data. The integration of these sources into personality-centric models has the potential to transform them into real-time predictive models, enabling deeper and more dynamic profiling. This, in turn, would not only augment credit scoring accuracy but also facilitate improved customer management, thereby promoting financial well-being.

In summary, while this study contributes valuable insights, it is essential to recognise its limitations and to pursue future research avenues that address these constraints, thereby advancing the field of personality-centric credit scoring.

## CONCLUSION

In a world increasingly affected by crises and high inflation rates, it is crucial to prioritise responsible financial inclusion for those impacted. Traditional credit assessment methods that rely on financial data often prove inadequate or unreliable in such situations. Moreover, specific vulnerable groups in Western societies, including migrants, young individuals, divorced individuals, those with illnesses, fixed-income seniors, start-up entrepreneurs and sole traders, encounter difficulties in accessing financial assistance even outside of crisis situations.

This research underscores the significance of considering an individual's personality as an alternative approach when conventional credit scoring methods prove insufficient in unstable market conditions. Through an analysis of a representative sample of low-income individuals in the USA and the Netherlands, our regression model identifies various factors contributing to late payment behaviour, including financial acumen, confidence level, financial vulnerability optimism, impulse control, emotional spending propensity and age.

By leveraging this insight, (neo)banks can actively promote responsible financial inclusion for vulnerable customers. Thus, when applicant data is limited, unreliable or entirely absent, personality data assessing an applicant's financial personality can be utilised to make well-informed lending decisions. This approach enables lenders of all types to support individuals lacking conventional credit history or facing exceptional circumstances, facilitating their access to essential financial resources. Incorporating psychometric data into their evaluation processes, financial institutions can contribute to a more inclusive and resilient financial landscape.

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